REMARKS

I. INTRODUCTION

This application stands with claims 1-21, 25-28, 31-37, and 50-51 where claims 1, 8, 13, 26, and 32 are independent claims. Applicants amended claims 1, 8, 13, 25, 26, and 32 to overcome the rejections and added new claims 52-54 for the reasons explained below.

Applicants also thank the Examiner for indication that claims 7 and 37 are allowable.

II. INDEFINITENESS REJECTION UNDER 35 USC §112

Claims 1-21, 25-28, 31-37, and 50-51 stand rejected under 35 U.S.C. §112, second paragraph as being indefinite for reciting the words "ordinal count". In response, Applicants amended independent claims 1, 8, 13, 26, and 32 to replace the words ordinal count with a more specific explanation. For example, claim 1 now recites:

> ... assigning each training vector a sequence number according to the ordering to form the 'x' dimension of the data with the sequence numbers; ....

Claims 13 and 32 recite similar features in terms of vectors, while claims 8 and 26 respectively recite this feature in terms of observations and snapshots. These amendments are fully supported by the specification (*see* page 14, lines 29-30). The sequence number is merely a place holder to show the location of the vector along the x-axis. Accordingly, Applicants submit that this rejection of independent claims 1, 8, 13, 26, and 32, and their rejected dependent claims, under 35 USC §112, second paragraph, has been overcome, and respectfully request withdrawal of the rejection.

III. SUBJECT MATTER REJECTION UNDER 35 USC §101

Claims 1-7, 13-21, and 25 stand rejected under 35 U.S.C. §101. In response, Applicants amended claims 1 and 13 to recite a method of monitoring an object instrumented with sensors. Claims 1 and 13 now relate to a transformation of sensor readings or signals into a training set of vectors, and to a particular device for monitoring an object instrumented with sensors. This amendment is supported throughout the specification (*see, e.g.*, page 1, lines 21-23). For this reason, Applicants submit that the rejection of claims 1 and 13, and their dependent claims, under 35 U.S.C. §101 has been overcome, and respectfully request that this rejection as to those claims be withdrawn.

IV. OBVIOUSNESS REJECTIONS

Claims 1, 4, 6, 8, 11-15, 17, 26, 27, 31, 32, 34, 36, and 51 stand rejected under 35 U.S.C. §103(a) as being unpatentable over Black (Black, Christopher L.; Uhrig, Robert E.; Hines, J. Wesley; "System Modeling and Instrument Calibration Verification with a Nonlinear State Estimation Technique", Maintenance and Reliability Conference Proceedings, May 12-14, 1998) in view of Dougherty (James Dougherty et al., "Supervised and Unsupervised Discretization of Continuous Features", 1995, in "Macine Learning: Proceedings of the Twelfth international Conference" ed. Armand Prieditis and Stuart Russell, Morgan Kaufmann Publishers, nine unnumbered pages).

Claims 2, 3, 5, 9, 10, 19-21, 25, 28, 33, 35, and 50 stand rejected under 35 U.S.C. §103(a) as being unpatentable over Black in view of Dougherty and U.S. Patent No. 5,764,509 (Gross).

Claim 16 stands rejected under 35 U.S.C. §103(a) as being unpatentable over Black in view of Dougherty and U.S. Patent No. 6,941,287 (Vaidyanathan).

Claim 18 stands rejected under 35 U.S.C. §103(a) as being unpatentable over Black in view of Dougherty and Hussain (F. Hussain et al., "Discretization: An Enabling Technique", June 1999, The National University of Singapore, pp. 1-27).

In response to all of these rejections, Applicants respectfully traverse because, first, the cited references, alone or in combination, do not disclose or suggest "selecting at least one vector from each of the equally spaced ranges while selecting less than all of the training vectors of the equally spaced ranges for training the adaptive model" as now recited in claim 1, and similarly recited in claims 8, 13, 26, and 32 (albeit related to intervals or bins instead of ranges). These amendments are fully supported by the specification (*see, e.g.*, p. 10, lines 18-23).

In the present application, bins are used to identify a subset of representative values from continuous signals providing the values (*see* p. 15, lines 1-3). Each representative value thus identified references a moment in time in which the sensor value was recorded. The values of other modeled sensors which were recorded at that time collectively constitute an observation, vector and/or "snapshot". Thus, in the present application, a subset of observation vectors are selected from a large data set of observation vectors, such that the observation vectors selected contain representative values from each of the continuous signals included in the model. This subset of observation vectors forms the "training set" of vectors that are actually used to train the model. The original set of observation vectors can be quite large, typically containing many thousands of vectors. The training set of observation vectors produced by the invention is much smaller, typically containing tens of vectors. See page 10, lines 18-23 of the present application.

In contrast, Dougherty merely discloses machine learning algorithms where all records in a bin and in the original set are used to train the pattern recognition algorithms. Putting it another way, Dougherty discloses that following the application of the equal width interval binning algorithm to transform continuous-valued signals to

discrete-valued signals, the machine learning algorithms use all elements of the discrete-valued signals to train the pattern recognition algorithms. This is understood by those of ordinary skill in the art from the types of algorithms recited in Dougherty. Nothing in Dougherty suggests using only certain records from each bin. Thus, this binning process in Dougherty is nothing like the presently claimed process for distilling or reducing the number of vectors for a training set by selecting certain vector or vectors in each bin.

The other cited references (Black, Gross, Hussain and Vaidyanathan) do not disclose or suggest these features related to selecting less than all of the vectors in a bin as now recited in similar terms in claims 1, 8, 13, 26, and 32 either.

Since none of the cited references disclose selection of less than all of the vectors in a bin and/or defined range for training as similarly recited in claims 1, 8, 13, 26, and 32, Applicants submit that the 35 U.S.C. §103(a) rejection of independent claims 1, 8, 13, 26, and 32, and their rejected dependent claims, based on Black and Dougherty alone or in combination with Vaidyanathan, Hussain, and/or Gross, have been overcome. Thus, Applicants respectfully request that these rejections of claims 1, 8, 13, 26, and 32, and their rejected dependent claims, be withdrawn.

Second, Applicants respectfully traverse because the cited references, alone or in combination, do not disclose or suggest "training the adaptive model . . . with training calculations that use sensor reading values from the signals that form the vectors" as now recited in claim 1 and similarly recited in claim 13 (this features was also added in claims 52-54 as explained below). In the present application, the sensor values that form the vectors, observations, and/or snapshots are used without transformation for selecting vectors and for use in training calculations. In one example, sensor values that are closest (in absolute difference) from the interval boundary values are identified and used directly to train the model without alteration (*i.e.*, discretization) (*see* p. 8, lines 25-26, and p. 15, lines 2-6 and 27-30).

In contrast to the present application, Dougherty discloses discretization, which means that the bin number values, or other pre-assigned values, are used instead of the actual sensor reading values for training, and thus, the data in the sensor signal are mathematically transformed from a set of real numbers to a set of discrete values that are drawn from a finite set of integers. More specifically, Dougherty discloses the efficacy of various machine learning algorithms, one of which is the equal width interval binning algorithm (Section 3.1 of Dougherty), as they apply to decision tree and classification pattern recognition algorithms. These pattern recognition algorithms require that the data they act upon take discrete values. This means that each signal (or feature as termed in Dougherty's paper) analyzed by the algorithm consists of a finite set of values, which are typically integers. The equal width interval binning algorithm is used to "discretize" a continuous-valued signal. Continuous-valued signals include time-series data from sensors such as those sensors encountered in equipment and process monitoring. When applied to a sensor signal, the equal width interval binning algorithm produces a finite set of equally-spaced intervals that span the range of values in the signal. All sensor signal values that fall in a particular interval (i.e., bin) have their values replaced by a discrete value, typically being the bin number as well understood by those of ordinary skill in the art.

It should be noted that it makes no difference that equal width interval binning is an unsupervised discretization method. Unsupervised methods do not use instance labels (e.g. bin numbers of each bin or any other pre-assigned number) for *establishing* the intervals in contrast to supervised methods, but both methods transform the values in the bins, such as sensor reading values, to, typically, the bin number so that these bin numbers are used for the training calculations rather than the sensor reading values (*see* page 1 of Dougherty, last paragraph paragraph).

Since the point of Dougherty is to use bins in order to discretize values as explained above, it makes no sense to combine Dougherty with the other cited

references (Black, Gross, Hussain and/or Vaidyanathan) where they suggest a completely different training system that uses the sensor reading values rather than systems using discretized values.

For the additional reasons mentioned above, Applicants submit that the 35 U.S.C. §103(a) rejection of independent claims 1 and 13, and their rejected dependent claims, based on Black and Dougherty alone or in combination with Vaidyanathan, Hussain, and/or Gross, have been overcome. Thus, Applicants respectfully request that these rejections of claims 1 and 13, and their rejected dependent claims be withdrawn.

IV. OTHER CLAIM AMENDMENTS

Dependent claim 25 has been amended for consistency to claim 13. Specifically, claim 13 recites steps a) through f). Claim 25, which depends from claim 13, has been amended to recite steps g) through k) instead of steps f) through j).

Dependent claims 52-54 have been added to recite the feature of training by using sensor reading values that form the vectors, observations, or snapshots and to use the sensor reading values in calculations to train the adaptive model as similarly explained above for claims 1 and 13. Claims 52-54 respectively depend from claims 8, 26, and 32. These amendments are fully supported by the specification (*see* p. 8, lines 25-26, and p. 15, lines 2-6 and 27-30). No new matter was added to amend these claims.

V. CONCLUSION

In view of the foregoing, Applicants respectfully request reconsideration and allowance of all pending claims. The Examiner is invited to contact the undersigned attorney to expedite prosecution.

Respectfully submitted,

FITCH, EVEN, TABIN & FLANNERY

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